IJCSE International Journal of Computer Sciences and Engineering Open Access

Research Paper Vol.-6, Issue-5, May 2018 E-ISSN: 2347-2693

Underwater Image Restoration Based on Illumination Normalization and Deblurring

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Available online at: www.ijcseonline.org

Accepted: 23/May/2018, Published: 31/May/2018

***Abstract* -** The fundamental reason for submerged image handling is to enhance submerged image enhancement. The preparing of submerged image caught is essential in light of the fact that the nature of submerged images influence and these images drives some significant issues when contrasted with images from a clearer domain. Because of the presence of clean particles in the water, submerged images suffer from the backscattering impact. To overcome this drawback I propose the new method called illumination normalization and deblurring of underwater image restoration. In this paper propose, first estimate the illumination directions of underwater images and cope with the problem of illumination normalization. Secondly deblurring of the underwater image using deconvolution algorithm and finally by the fusing both the results the restored image is acquired.The quality of the enhanced image is evaluated by using the metric is called blind/reference less image spatial quality evaluator (BRISQUE).

***Keywords* -** Image Restoration, Illumination Direction, Illumination Normalization, Deblurring, Deconvolution

I. INTRODUCTION

Underwater image suffers from some trouble such as incomplete range of visibility, blur, low contrast and color, bright artifacts, noise, appearance of haze and non-uniform lighting. Innovation propels in kept an eye on and remotely worked submersibles enable individuals to gather images and recordings from an extensive variety of the undersea world. Obtaining high quality underwater images has very important applications. Clearer underwater images or videos can assist in ocean engineering such as oil drilling and subsea exploration. Besides, it can also be used for marine scientific research such as studying the marine organisms or analyzing marine geological environment.

Because of the presence of tidy like particles in the water, submerged images or recordings dependably experience the ill effects of the backscattering impact. Light reflected from objects propagates toward the camera, part of the light may be scattered by the floating particles such as sand, minerals, and plankton that exist in lakes, oceans, and rivers. This results in the haze-like effect for underwater images and greatly reduces the scene contrast. Submerged images are basically described by their poor perceivability on the grounds that the light is lessened through the water and the image result inadequately differentiated.

The retention and dispersing procedures of the in water impact the general execution of submerged imaging framework. Forward dissipating by and large prompts obscuring of image highlights. At increasing depth the ambient light is attenuated to where colors can no longer be distinguished and eventually to effective darkness. Artificial light source must subsequently to beused to illuminate the scene, these source contribute to scattering and introduce beam pattern artifacts in the image.

The last paragraph of Introduction specifies the overview of underwater image restoration. Rest of the paper is organized as follows, Section I contain the introduction of nature of underwater images, Section II contain the related work of various methods of underwater image enhancement, Section III contain the proposed work methodology of illumination normalization and deblurring, Section IV highlights results and discussion of various images, Section V contain the measures of test images and restored images, conclusion and future scope are stated in SectionVI.

II. RELATED WORK

The current research demonstrates that submerged images raise new difficulties and force critical issues because of light retention and diffusing impacts of the light and inborn structure less environment. Histogram Equalization [1] is a simple and effective image enhancement technique. But, it tends to change the mean brightness of the image to the middle level of the permitted range [2], and hence is not a very suitable for consumer product. While preserving the original brightness is essential to avoid annoying artifacts. In [3], Wavelength Compensation and dehazing,to expel mutilations caused by light disseminating and shading change.The dehazing calculation and wavelength pay are used to evacuate the cloudiness impact and shading change along the submerged proliferation way to the camera.

The dull channel earlier [4], depends on the measurements of open air cloudiness free images. In most of the local regions which do not cover the sky, some pixels (called dark pixels) very often have very low intensity in at least one color (RGB) channel. In hazy images, the intensity of these dark pixels in that channel is mainly contributed by the air light. In this way, these dull pixels can specifically give a precise estimation of the cloudiness transmission. Joining a cloudiness imaging model and a delicate tangling insertion technique, recuperate a top notch dimness free image and deliver a decent profundity delineate. Red Channel method [5], suitable for underwater images, which can be specified as a variant of the Dark Channel method is employed in dehazing of atmospheric images. This method is simple and robust, and it recovers part of the lost visibility range while correcting the color distortion produced by absorption. Another submerged optical model [6], to depict the development of submerged images and present a powerful submerged image upgrade technique, that utilizations submerged dull channel preceding evaluation the diffusing rate and the transmission of blue and green light.

The inherent optical properties from background color of underwater images [7], are based on the fact that there is a relationship between background light and inherent optical properties in underwater imaging. An underwater imaging model under natural illumination is formed. The global background light does not depend on the object–camera geometry, but on the inherent optical properties and camera properties. Based on the model of global background light, derive the inherent optical properties. In a Dark channel prior method [8], this approach is based on a statistically independent assumption in a local patch, it requires the independent components varying significantly. Any lack of variation or low signal-to-noise ratio (e.g., in dense haze region) will make the statistics unreliable. Moreover, as the statistics is based on color information, it is invalid for gray scale images and difficult to handle dense haze which is often colorless and prone to noise.

In a Red-Dark Channel Prior (RDCP) [9], the intensity of the dark channel can roughly estimate the quality of the haze. After comparing the high and low visibility properties in underwater images, observed that the intensity in red is easily affected by the influence of attenuation. The background light is then estimated by choosing the pixel values that are below 10%. After estimating the background light, estimate the transmission of the whole image by normalizing and minimizing in a local patch. [10], introduces the best method that is able to enhance underwater images, as well as videos by fusion-based approach, does not require multiple images, deriving the inputs and the weights only from the original degraded image. Instead of directly filtering the input image, developed a fusion-based scheme is driven by the intrinsic properties of the original image (these properties are represented by the weight maps). In this framework the degraded image is firstly white balanced in order to remove the color casts while producing a natural appearance of the sub-sea images. The second input is derived from this filtered version in order to render the details in the entire intensity range. The fusion based enhancement process is driven by several weight maps. These weights assign higher values to pixels to properly depict the desired image qualities.

To preserve temporal coherence in videos, apply temporal bilateral filtering between adjacent frames.In [11], the main contribution is the proposal of a depth prior that exploits the wavelength dependent attenuation of light in water to estimate the depth of a scene from a single image, then use this depth information to recover the scene radiance from the hazy image by modeling the true scene radiance as a Markov Random Field (MRF), which can be estimated using a maximum a posteriori *(*MAP) estimator. The estimate of the air light includes the effects of absorption on the air light, i.e. the air light is blue, not white. Therefore, when removing the additive air light the color balance of the imagery is improved.

In weighted guided middle channel [12], technique incorporates a viable submerged scene improvement conspire and a shallow water imaging model that adjusts for the constriction disparity along the spread way. The enhanced images are portrayed by a diminished noised level, better presentation of the dim districts, and unrivaled worldwide complexity where the finest subtle elements and edges are improved significantly. [13], gauge scene profundity by means of image fogginess. This uses the end by morphological remaking (CMR), which requires less calculation cost and furthermore diminishes the possibility of mistaken haziness engendering. Toward the end, the assessed profundity outline image fogginess is embraced in the IFM to reestablish and upgrade submerged images for better visual quality in various lighting conditions. Retinex-based enhancing approach [14], is proposed to enhance single underwater image. There are mainly three steps to enhance an underwater image. First, a simple but effective color correction strategy based on a statistical approach is adopted to address the color distortion. Then a variationretinex model is built to decompose the reflectance and the illumination from the luminance of the color correction image. Third, since the reflectance and the illumination represent the detail and brightness respectively, two methods based on histogram are used to enhance the reflectance and the illumination. The enhanced image is obtained by combining the enhanced reflectance and the enhanced illumination.

In [15], elegantly relate the effects of skew to motion blur through a careful investigation and under pinning of the physics of the image formation process. First part, describe the image formation model for Unidirectional Cyclic Waves (UCW) and a scaled orthographic camera, and derives an expression for the geometric warp at a pixel in the image. Unlike the UCW, the set of transformations induced by these waves on the image plane is space-variant. Start with an analytical model for circular ripples and transforming the blurred. Begin with an explanatory model for round swells and changing the obscured. Shading constriction earlier for single imagedehazing [16], is a straightforward and intense earlier can make a direct model for the scene profundity of the dim image. By taking in the parameters of the direct model with a regulated learning technique, the scaffold between the foggy image and its relating profundity delineate constructed viably. In [17], in light of versatile wavelet joining versatile limit determination with versatile edge choice with versatile yield of the edge function.In this, first mulling over the submerged image with low flag to commotion proportion (SNR), differentiate unevenness and poor image quality. After this the subsequent stage is some pre-preparing ought to be done before wavelet edge denoising. At that point, they receive versatile wavelet consolidating versatile limit determination with versatile yield of the edge work for the image de-noising. At long last the recreation comes about demonstrate that this strategy not just evacuates clamor adequately, enhances image yield crest motion to-commotion proportion (PSNR), yet additionally yields prevalent vision quality.

III. METHODOLOGY

The system architecture of the proposed method describes the basic procedure for estimating the illumination directions of underwater images and cope with the problem of illumination by normalization. Secondly deblurring of the underwater image using deconvolution algorithm and finally by fusing both the results the restored image is acquired.

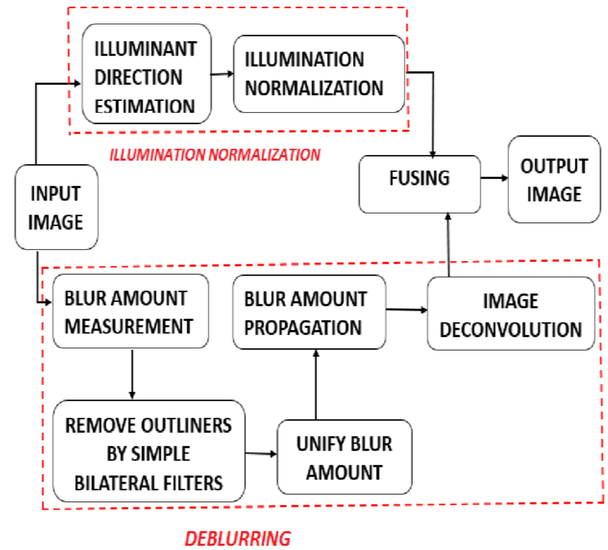


Figure 1. Proposed method Block diagram

A. Illuminant Direction Estimation

The reason why we need to estimate the illuminant directions of images is different regions in images make different contributions to illuminant direction estimation. For example, the smooth regions play a more important role than the concavo-convex ones usually the smooth regions have similar textures and simple edges, whereas the concavo–convex regions have opposite characteristics. So it is worthwhile to find out regions with simple edges for illumination direction estimation. In order to better describe our method, we list the basic six steps of the method, as shown below:

1. Adjust the sizes of images (color or grey) to a uniform value.
2. Use the Canny edge detector to find object boundaries in the luminance component and get the binary edge image.
3. Divide the binary edge image and the luminance component into sixteen local regions.
4. For each local region, analyse its complexity depending on the edge level percentage and calculate its average grey value.
5. Estimate the illumination directions of the three selected local regions with less complexity and large average grey value.
6. Synthesize the three illuminants directions and transform the result to the final illumination direction in the original image (color or grey).

In all the steps mentioned above, the local region complexity analysis and illumination direction estimation are particularly important.

B. Illumination Normalization

A description of image complexity analysis based on the edge level percentage which is defined by,

$$\Psi=|A|/(\text{width}\times\text{height})A=\{p(x,y)/p(x,y)=1\} \quad (1)$$

Where |•| indicates cardinality of a set, p(x,y) denote the gray value at pixel (x,y), and width × height is the dimension of the image. After receiving the edge level percentage of each local region, we calculate the average gray value of each local region, and then select three local regions with less complexity and large gray value for estimating the illuminant direction that aims to achieve a higher recognition rate in less execution time. After determining the range of gray levels stretch the range of gray levels into the dynamic range of display device. Finally, achieve illumination normalization.

C. Blur Amount Measurement

Using the distance between the maximal value and minimal value of a second derivative to define the blur amount for each pixel in the blurred object. In the detailing of an obscured step edge, can be spoken to as the obscure sum. We can compute σ by utilizing are obscure strategy. In the blurred step edge formulation, can be noteted as the blur amount. By using are blur method, we can calculate σ. The blur of the blurred step edge i(x) is

$$i_1 \ (x)=(x)\otimes g(x,\sigma) \quad (2)$$

$$\frac{A}{\sqrt{2\pi(\sigma^2+\sigma_0^2)}}\exp(-\frac{x^2}{2(\sigma^2+\sigma_0^2)}) \quad (3)$$

Where $\sigma 0$ is standard deviation of deblurr Gaussian function. Then the blurred step edge divided by deblurr blurred step edge, we get the following equation,

$$\frac{|\nabla i(x)|}{|\nabla i_1(x)|}=\sqrt{\frac{(\sigma^2+\sigma_0^2)}{\sigma^2}}\exp(-\left(\frac{x^2}{2\sigma^2}-\frac{x^2}{2(\sigma^2+\sigma_0^2)}\right)) \quad (4)$$

Let R be the ratio of blurred step edge to deblurr blurred step edge. When$x$=0 Rhas maximum value.

Then we have,

$$R=\frac{|\nabla i(x)|}{|\nabla i_1(x)|}=\sqrt{\frac{(\sigma^2+\sigma_0^2)}{\sigma^2}} \quad (5)$$

Given a ratio R, the unknown σ can be computed using

$$\sigma=\frac{1}{\sqrt{R^2-1}}\sigma_{0.} \quad (6)$$

While σ is computed, we use σ as the blur amount at edge pixel.

D. Blur Amount Refinement

Propagate the blur amount to non-edge pixels. Remove the outliers to obtain sparse measurement results. (Pixels in a sparse matrix are often zero). Therefore, propose a simple bilateral filter for sparse blur measurements. (The main idea is that only nonzero value pixels are considered in filter procedure.)

After the blur amount of edges pixels has been computed, we propagate the blur amount to non-edge pixels for which blur amount have not previously been computed. However, phenomena such as shadows and highlights may cause some outliers to appear in the measurement results. These outliers may propagate incorrect results. We should remove these outliers to obtain sparse measurement results. Pixel sin a sparse matrix are often zero. Therefore, instead of using a cross-bilateral filter, such as that applied in, we propose using a simple bilateral filter for our sparse blur measurements. The main idea is that only nonzero value pixels are considered in filter procedure. The definition of a simple bilateral filter, which is applied only to nonzero pixels, is as follows:

$$W_{p=}\sum_{x_i\varepsilon\Omega} W_r\,(x_i)W_s(x_i) \quad (7)$$

And the weighting functions WR andWS are defined as

$$W_R(x_i)=f_r(\left|\left|I(x_i)-I(x)\right|\right|) \quad (8)$$

$$W_s(x_i)=g_s(\|x_i-x\|) \quad (9)$$

Where $Ifiltered$ is the sifted result, I is the inadequate obscure estimation to be separated, are the directions of the present pixel to be sifted, Ω is the window focused in x and (xi) must be none zero value,fr is the range part of Gaussian capacity for smoothing contrasts in forces, and gs is the spatial bit of Gaussian capacity for smoothing contrasts in facilitates. The word on the rooftop is smoother after utilization of a straightforward two-sided channel.

E. Unify Blur Amount

The obscure measures of pixels that are situated in the same inflexible protest are equivalent. In this way, we utilize k-implies bunching to bring together the estimation comes about. K-implies bunching calculations limit the inside group wholes of squares. Accordingly k-implies strategies bunch the pixels with a similar obscure sums together. Marks of every pixel at the edge area are figured by limiting the accompanying cost work:

$$arg_s min \sum_{i=1}^{k} \sum_{x_j \varepsilon s_i} \|x_j - \mu_i\|^2 \qquad (10)$$

Where S={$s1$,$s2$… ..sk}is an arrangement of clusters,$k$is the coveted number of sets, and μi is the mean of focuses in si.We apply morphological activities to the refinement result, and we watch that k-implies grouping effectively brings together the obscure sum in an unbending item.

F. Blur Amount Propagation

To spread an expected obscure add up to an entire image, we apply the tangling laplacian insertion technique to assessed obscure estimation. The estimated obscure sums from the edge districts are proliferated to other non - edge locales to frame a defocus delineate. The cost capacity of the tangling laplacian is

$$E(d) = d^T \text{ Ld}+\lambda(\text{d-}\hat{d})^T \text{ D(d-}\hat{d}) \qquad (11)$$

Where d is the full defocus outline, ̂is the vector types of the scanty defocus delineate, is the tangling Laplacianmatrix, and D is askew network whose component Dii is 1 at edge districts and 0 generally and λ is parameter which adjusts devotion to the inadequate profundity guide and smoothness of introduction. The defocus guide can be gotten by explaining, the proposed defocus guide and Zhuo's defocus outline evaluated obscure sums are distinctive at various parts of the obscured thusly, it is hard to section the obscured part. By differentiate, for the proposed defocus delineate, key advantage from our uniform defocus outline the obscured part.

G. Image Deconvolution

In general the image deconvolution is performed basically by reading the input sample image, the image is being simulated to blur then restore the blurred image Using PSFs of various sizes attended by analysing the restored PSF and improving the restoration by using additional constraints on the PSF restoration.

The point spread function (PSF) describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response, the PSF being the impulse response of a focused optical system the point spread function (PSF) describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response, the PSF being the impulse response of a focused optical system

$$\text{PSF (f,z)}= I_r\text{(0,z,f) exp (-z}\alpha\text{(f)-}$$

$$2\rho^2/\left(0.36\frac{cka}{NAf}\sqrt{1+\left(\frac{2ln2}{c\pi}\left(\frac{NA}{0.56k}\right)^2\ fz\right)^2}\right) \qquad (12)$$

Where k-factor depends on the truncation ratio and level of the irradiance, NA is numerical aperture, c is the speed of light, f is the photon frequency of the imaging beam, Ir is the intensity of reference beam, a is adjustment factor and is the radial position from the center of the beam on the corresponding z-plane.

In mathematics, a blurred image can be modeled as

$$B=I*K+N \qquad (13)$$

Where B is blurred image, $*$ is convolution operator, I is latent unblurred image, is PSF, and $N$is noise in image. The equation can then be represented as follows according to Baye'stheorem:

$$(I,K|B)\propto(B|I,K\ )p(I)p(K) \qquad (14)$$

Where (B|I,) speaks to the probability and (I) and (K) mean the priors on the idle image and PSF. In the PSF estimation step Bayes'theorem can be changed into the accompanying conditions:

$$\acute{K}=arg_K\ min\ \ \{\|K*I-B\ \|+(K)\} \qquad (15)$$

$$\acute{I}=arg_I\text{min}\ \ \{\|K*I-B\ \|+pI(I)\}. \qquad (16)$$

Considering the gradient of latent image and blurred image while solving kernel estimation problem, we rewrite it as the following energy function:

$$\text{E}(K)=\sum\|\text{K}*\partial_* \text{L-}\partial_* \text{B}\|^2+\beta\|\text{K}\|^2 \qquad (17)$$

$$\text{E}(L)=\sum\|K*L-B\ \|^2+\alpha\|\nabla L\|^2, \qquad (18)$$

where$\partial_*\in\{\partial x, \partial y, \partial xx, \partial xy, \partial yy\}$is the partial derivative operators in different directions, ∇is Sobel operator, and α and β are preset parameters. We iteratively settle the first conditions to get an exact PSF. To quicken the PSF estimation process, we apply a stun channel before every PSF estimation step. The plan of the stun channel is characterized as takes after:

$$I_{t+1} = I_t - sign(\Delta I_t)\|\Delta I_t\|d_t \qquad (19)$$

Where It is the image at current cycle, It+1is the image at next iteration,δIt is the guide got from Laplacian administrator at emphasis t,∇It is the angle of I at current iteration,and$dt$is time step.

IV. RESULTS AND DISCUSSION

This chapter explains about the experimental results of Illumination normalization and Deblurrness. To show the best result of the proposed method we compare the results with various sample images.The first image is the input image,the second and third images shows the outcomes of illumination normalization and deblurring result from the deconvolution algorithm respectively. Final image is the restored image obtained by fusing the outcomes of second and third image. The BRISQUE score is obtained for both input and restored images. The implementation process is obtained using MATLAB R2016a and the images are in JPG format.

A. Input Images

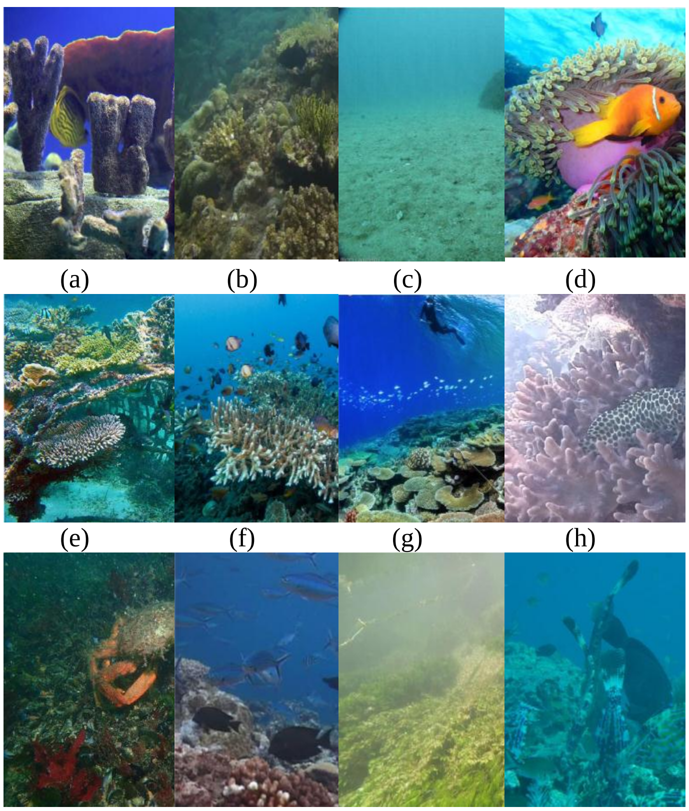

(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

Figure 2. (a-l) Input Images

B. Illumination normalization Images

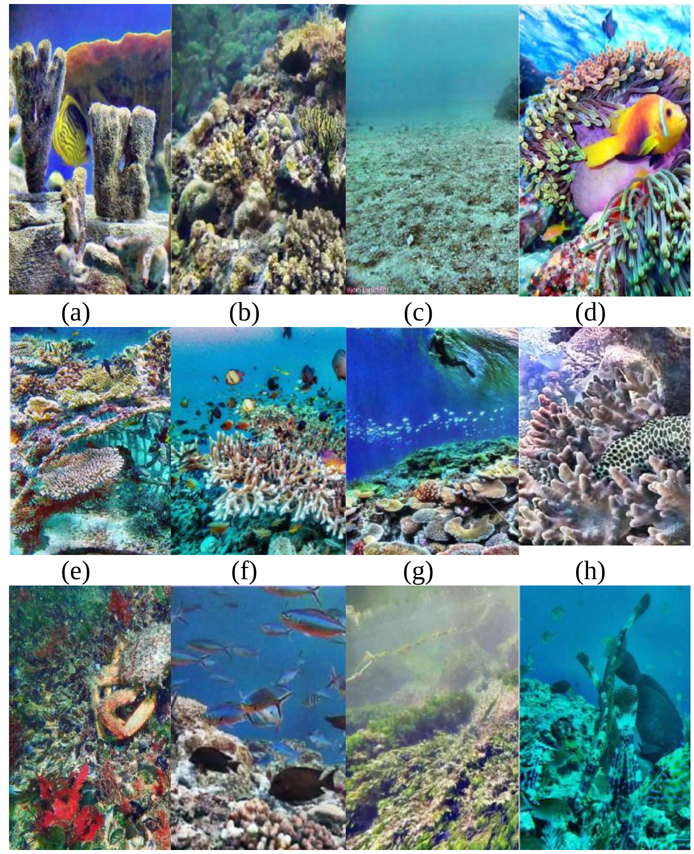
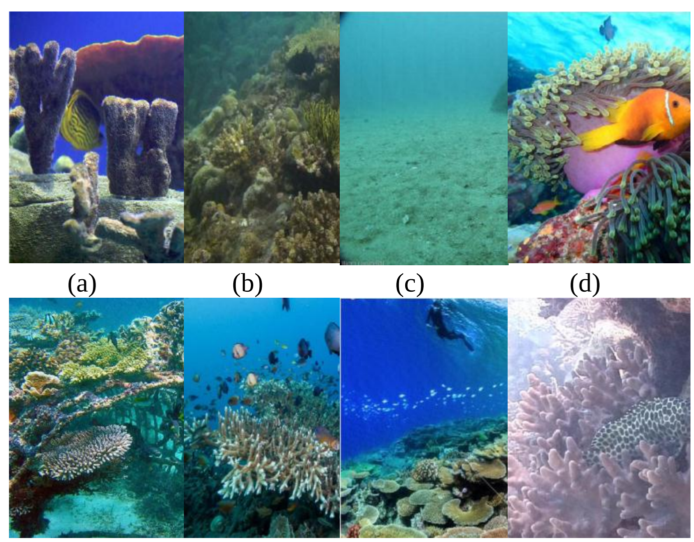

(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

Figure 3. (a-l) Illumination normalization Images

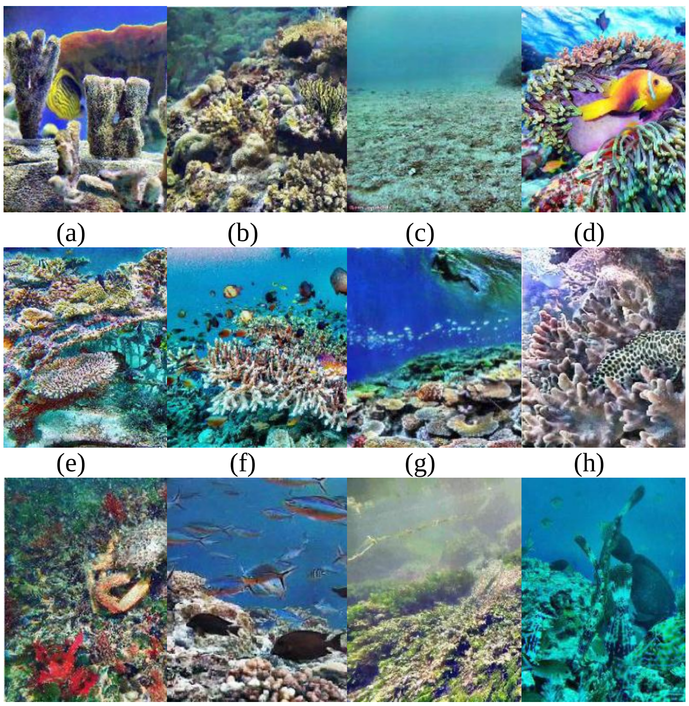
C. Deblurred Image


(a) (b) (c) (d)
(e) (f) (g) (h)

(i) (j) (k) (l)

Figure 4. (a-l) Deblurred Images

D. Restored Image



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

Figure 5. (a-l) Restored Images

V. BRISQUE MEASUREMENT

Blind/Reference less Image Spatial Quality Evaluator (BRISQUE) which removes the point insightful measurements of neighborhood standardized luminance flags and measures image instinctive nature (or scarcity in that department) in view of estimated deviations from a characteristic image display. We additionally demonstrate the circulation of pairwise measurements of nearby standardized luminance signals which gives contortion introduction data. In spite of the fact that multi scale, the model uses simple to register highlights making it computationally quick and time proficient. The edge work is appeared to perform factually superior to anything other proposed no reference calculations and full reference basic likeness file.

A. The BRISQUE Score

Image	Input Image	Restored Image
A	0.7316	0.8521
B	0.7856	0.8231
C	0.6468	0.8388
D	0.5861	0.6751
E	0.6160	0.7376
F	0.6102	0.6513
G	0.6707	0.8017
H	0.7192	0.7632
I	0.6230	0.7284
J	0.5918	0.7674
K	0.7690	0.7788
L	0.7199	0.7362
Average	0.6725	0.7628

Table 1. The BRISQUE score values

VI. CONCLUSION AND FUTURE SCOPE

We have proposed a technique to eliminate the presence of blurrness and restoration of underwater images that are affected by colour distortion that occur due to the dust-like particles in the water. Underwater images or videos always suffer from the backscattering effect. Light reflected from objects propagates toward the camera, part of the light may be scattered by the floating particles such as sand, minerals, and plankton that exist in lakes, oceans, and rivers. This results in the haze-like effect for underwater images and greatly reduces the scene contrast.
Submerged image is basically described by their poor perceivability in light of the fact that the light is weakened through the water and the image results ineffectively differentiated. The retention and diffusing procedures of the water impact the general execution of submerged imaging framework. Forward diffusing by and large prompts obscuring of image highlights. Forward scattering generally leads to blurring of image features. At increasing depth the ambient light is attenuated to where colors can no longer be distinguished and eventually to effective darkness. Artificial light source must subsequently be used to illuminate the scene, these source contribute to scattering and introduce beam pattern artifacts in the image.

In our method, the given entire image is divided into 16 local regions. To improve the accuracy of illuminant direction estimate and speed up the estimation procedure, the three local regions, which meet the requirements of lower complexity and larger average gray value, are selected to calculate the final light source direction.We propose a uniform defocus delineate image division. We fragment the obscured image into obscured areas and unblurred districts by utilizing the proposed uniform defocus outline. Each obscured area is dissected to acquire a gauge of its PSF. Each obscured district and its PSF are then entered as contributions to a uniform movement obscure image deconvolution calculation. At last, by melding both the results of brightening standardization and deblurred image the resultant re-established image is being got. Finally, by fusing both the outcomes of illumination normalization and deblurred image the resultant restored image is being obtained.

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